

The Impact of Recreational Marijuana Legalization on Financial Leverage*

Yung-Hsuan Chang^a, Keng-Yu Ho^{a, b} and Yanzhi Wang^{a, b}

^a *Department of Finance, College of Management, National Taiwan University, Taiwan*

^b *Center for Research in Econometric Theory and Application, National Taiwan University, Taiwan*

Abstract

This study adopts a health economics perspective to investigate the impact of marijuana use on a firm's capital structure decision, using the staggered implementation of Recreational Marijuana Laws (RMLs) as an exogenous shock. We observe a notable rise in corporate leverage for firms located in states that have enacted RMLs. Our study finds that the increase in leverage is particularly evident in technology firms, firms in states with lower tobacco tax rates, and firms with lower executive salaries. The rising incidence of marijuana usage and its negative effects on managers' or shareholders' cognitive function are two potential factors that driving firms to choose higher financial leverage. Moreover, we find additional evidence supporting a decline in profitability for firms located in RMLs states and characterized by high leverage.

JEL classification: G32; G38; G41.

Keywords: Financial Leverage; Recreational Marijuana; Health Economics.

* We are grateful for comments from Yan-Shing Chen, Kenneth Huang, Chih-Yung Lin, Tse-Chun LIN, Hong-Yi Chen, Chia-Wei Yeh, and conference participants in 2025 Taiwan Finance Association Annual Meeting. This work was financially supported by the Center for Research in Econometric Theory and Applications (Grant no. 114L900203) from Higher Education Sprout Project - The featured Areas Research Center Program by the Ministry of Education (MOE) in Taiwan. This work was also supported by Ministry of Science and Technology in Taiwan (NSTC 113-2410-H-002-024-MY3).

Corresponding author: Yanzhi Wang.

E-mail addresses: d11723002@ntu.edu.tw (Y. Chang); kengyuho@ntu.edu.tw (K. Ho);

yzwang@ntu.edu.tw (Y. Wang).

Work phone number: +886-2-33661094 (Y. Chang); +886-2-33661094 (K. Ho); +886-2-33661075 (Y. Wang).

1. Introduction

In a world where policy decisions ripple through the economy like unpredictable waves, the legalization of recreational marijuana in the United States presents a particularly intriguing case. According to data from the National Institute on Drug Abuse (NIDA) and the Centers for Disease Control and Prevention (CDC), as of 2022, the number of individuals who use marijuana daily or nearly daily has reached approximately 17.7 million, surpassing the 14.7 million individuals who consume alcohol on a daily basis. This shift highlights the growing trend of cannabis use and has made it one of the most commonly used psychoactive substances that alter brain function in the United States. Meanwhile, smoking marijuana not only has negative effects on human health, but the CDC also points out that secondhand cannabis smoke contains many of the same toxic and cancer-causing chemicals found in tobacco smoke.

Marijuana use is not solely a cultural or public-health matter but also an issue with significant economic and corporate implications. Marijuana use can reduce productivity through its effects on health and job performance (Arora, 2001; Goetzl et al., 2003; Loeppke et al., 2009). Although laws protect off-duty marijuana use, they raise concerns about workplace safety and productivity.¹ Additionally, marijuana use may impair cognitive functioning of brain (Bolla et al., 2002; Lahanas & Cservenka, 2019; Meier et al., 2012) and induce a more optimistic outlook (Wickens et al., 2019; Aloï et al., 2021). This pattern extends beyond low-income users to middle- and high-level executives.² Marijuana-induced shareholder optimism may also influence managerial decisions, as firms often respond to the expectations of nearby investors, for example through home bias phenomenon (Coval & Moskowitz, 1999). Thus, the recreational marijuana use influences financial decision-making at all levels, from the investment choices of individual investors to the strategic decisions of top executives. Historically, discussions have largely focused on prominent issues such as public safety, addiction, and taxation, while its impact on financial decision-making has received little attention (e.g., Chen et al., 2023). In this paper, our study explores the relationship between Recreational Marijuana Legalizations (RMLs) and corporate financial leverage, examining how managerial strategies, economic policies, and financial risks interact within this evolving landscape.

¹ California's AB 2188 law, which took effect on January 1, 2024, prohibits employers from terminating or penalizing employees for using marijuana during non-working hours.

² These including but not limited to Apple co-founder Steve Jobs, OpenAI CEO Sam Altman, former Google CEO Eric Schmidt, PayPal co-founder Peter Thiel, Tesla and SpaceX founder Elon Musk and Microsoft co-founder Bill Gates.

The legalization of recreational marijuana increases corporate leverage for the following reasons. First and foremost, cannabis use can affect physical health, impair cognitive flexibility, and executive decision-making (Curran et al., 2002; Meier et al., 2012), which can directly or indirectly lead to behavioral impairments, ultimately resulting in impulsive behavior (Gonzalez et al., 2012) or impaired decision-making (Pope & Yurgelun-Todd, 1996). Although individuals who use marijuana for recreational purposes may feel relaxed or euphoric, they may also exhibit an optimism bias (Wickens et al., 2019). Managers may exhibit an optimism bias in financial decision-making, which increases their inclination toward risk-taking. This tendency can undermine the ability of senior executives, board members, and management teams, including those in finance and accounting, to make well-informed and prudent decisions. Such effects can lead to cognitive biases, ultimately resulting in more risk-taking, more reckless, or less efficient decision-making. Next, based on the concept of home bias (Coval & Moskowitz, 1999), local residents are more likely to invest in firms within their region. If marijuana use makes residents more optimistic, leading them to perceive high corporate debt levels as sustainable, their risk aversion may decrease, thereby encouraging firms to take on more debt in their capital structure.

The staggered implementation of RMLs across different states provides an ideal setting for an empirical investigation on the effect of recreational marijuana use on corporate leverage. Using a sample of U.S. publicly traded firms from 2007 to 2022, we employ a staggered difference-in-differences (DiD) approach to compare firms in states that have enacted RMLs with those in states that have not, while controlling for firm-specific variables and macroeconomic factors. In our analysis, we primarily follow prior studies (Serfling, 2016; Bai et al., 2020) and employ propensity score matching (PSM) to mitigate endogeneity concerns. We show a significant increase in corporate leverage in the states that passing RMLs. Firms in the states passing RMLs have approximately 2% higher total debt to assets than firms in the states not passing RMLs, representing a 9% increase relative to the average leverage level. This increase corresponds to an average additional borrowing of \$132.98 million in total debt per firm. Our results support the hypothesis that RMLs may influence corporate decision-making and encourage greater risk-taking, making firms more inclined to increase their borrowing. We also implement multiple matching techniques, including radius matching, nearest neighbor matching, coarsened exact matching (CEM) and entropy balance matching. Notably, to address potential challenges related to staggered treatment adoption in the difference-in-differences framework, we employ the stacked DiD (Cengiz et al., 2019) and DiD imputation (Borusyak et al., 2024) approaches, which help account for treatment effect heterogeneity and avoid biases from improper comparison groups. All the results are consistent with our primary findings, which

indicate the robustness.

Next, we identify three key mechanisms through which RMLs influences corporate leverage. First, prior research highlights strong behavioral links between tobacco and marijuana use, with tobacco users significantly more likely to consume marijuana (Agrawal & Lynskey, 2009; Ramo et al., 2012). States with lower tobacco taxes tend to have higher smoking rates (Chaloupka & Warner, 2000), suggesting a larger base of potential cannabis consumers after legalization that firms headquartered in states with lower tobacco taxes may experience stronger leverage growth following passage of the RML. Consistent with this expectation, our empirical results indicate that firms located in states with lower tobacco taxes experience greater corporate leverage increases after the adoption of RMLs, supporting the complementary effects between marijuana and tobacco consumption, which drives corporate expansion. Second, technology firms tend to maintain low leverage due to their reliance on intangible assets and exposure to information asymmetry and cash flow volatility, which make debt financing more costly (Myers & Majluf, 1984; Hall, 2002). As a result, they adopt more conservative capital structures than asset-heavy industries (Frank & Goyal, 2009). Therefore, it is reasonable to infer that they have more room to increase leverage in states that adopt RMLs. Empirically, we do find that technology firms experience a more pronounced increase in leverage following the passage of RMLs. Third, the relationship between executive compensation and risk-taking behavior provides another avenue through which RMLs may influence corporate capital structure. Managers with lower salaries may be more inclined to take financial risks, as their personal financial incentives are less directly tied to firm stability. In contrast, highly compensated executives, who have more at stake in terms of long-term firm performance, may be more cautious in increasing leverage (Jensen, 1986; Sundaram & Yermack, 2007; Edmans et al., 2009). Consequently, firms with lower executive salaries may respond to RMLs with a greater willingness to assume additional debt, reflecting a higher tolerance for financial risk. Our empirical results reveal that firms with lower CEO compensation exhibited a more significant increase in leverage following the enactment of RMLs. This suggests that financial constraints on compensation may indeed influence leverage decisions.

Furthermore, we expand our analysis to investigate how RMLs affect corporate merger and acquisition (M&A) activities and firm risks. Our analysis finds that the passage of RMLs does not have a significant impact on firms' M&A events or stock return volatility, suggesting that regulatory changes related to marijuana legalization do not directly alter corporate expansion strategies or market risk perceptions. One possible explanation for the unchanged return volatility following the passage of RMLs

is a decline in innovation (Chen et al., 2023), coupled with an increase in leverage, resulting in an offsetting effect where one factor raises volatility while the other reduces it.

Finally, we posit that if firms increase their debt levels in response to RMLs without corresponding improvements in investment efficiency or revenue generation (Jensen & Meckling, 2019), they may face declining profitability over time. Most concerning, the risk-taking behavior associated with RMLs may not necessarily translate into productive innovation or long-term growth. Firms that take on excessive leverage due to altered managerial risk preferences may misallocate resources, engage in speculative investments, or fail to maintain optimal operational efficiency (Baker & Wurgler, 2002; Barberis & Thaler, 2003; Graham et al., 2013). This misalignment between financial decision-making and corporate performance could result in lower profitability, reduced returns on assets, and weaker overall financial health. Given these considerations, our hypothesis posits that firms in RMLs states are unable to achieve better operating performance compared to firms in states without legalized recreational marijuana, a claim substantiated by our empirical findings. The increase in leverage following RMLs does not enhance firm performance, indicating a misalignment between additional debt and optimal capital structure decisions.

This study contributes to the existing literature in three ways. First, it provides novel evidence linking social policies (i.e., RMLs in this paper) to corporate financial decisions, expanding the scope of research on the determinants of capital structure beyond conventional economic and market-based factors.³ Furthermore, the findings indicate that firms tend to increase leverage following the enactment of RMLs. However, this higher debt burden is unrelated to an increase in profitability, suggesting that firms may not be optimizing their capital structure despite taking on additional leverage. Second, adopting a health economics perspective (Grossman, 1972; Mahoney, 2015; Poterba et al., 2011), this study is a pioneering examination of how marijuana use influences corporate risk-taking behavior. By integrating insights from health economics and behavioral finance, it highlights the cognitive and psychological dimensions of managerial decision-making, offering a more comprehensive understanding of corporate financial behavior. Finally, this paper offers meaningful policy implications that social policy reforms can generate unintended yet economically significant shifts in firms' capital structures. Consistent with prior evidence showing that social and legal environments shape corporate financial decisions (Agrawal & Matsa, 2013; Xiong et al., 2021; Keum & Meier, 2024), our results suggest that policies

³ See survey in Frank & Goyal (2009); Rajan & Zingales (1995).

aimed at altering individual behavior may indirectly influence firm-level risk-taking, credit demand, and leverage choices.

The remainder of this paper is structured as follows. Section 2 provides a review of the relevant literature on capital structure theories, managerial decision-making, the economic implications of RMLs, and the institutional background of marijuana legalization in the U.S., leading to the development of our hypotheses. Section 3 details our data sources, variable construction, and empirical methodology. Section 4 presents our baseline regression results and robustness checks. Section 5 presents additional analyses, exploring the channels through which RMLs influence firm leverage, as well as its impact on firm performance and risk-taking behavior. Finally, section 6 concludes with a summary of our findings and suggestions for future research.

2. Literature Review, Institutional Background and Hypothesis Development

2.1 Capital Structure

The study of capital structure, rooted in Modigliani & Miller (1958) capital structure irrelevance theory, asserts that in a perfect market without taxes, financing decisions do not affect firm value. This framework is later revised to include corporate taxes (Modigliani & Miller, 1963), highlighting the tax shield benefits of debt but ignores the hidden worries caused by borrowing. Kraus & Litzenberger (1973) introduce financial distress costs. They rely on static trade-off theory, which balances tax benefits and distress costs to achieve optimal leverage, as empirically supported by Bradley, Jarrell & Kim (1984). Fischer, Heinkel & Zechner (1989) further develop dynamic trade-off models, accounting for adjustment costs and temporal deviations; the dynamic model can provide a more realistic view of firms' capital structure decisions.

Empirical studies have yielded mixed support for the trade-off theory. For instance, Frank & Goyal (2003) found evidence consistent with the theory in large firms but noted deviations among small firms, where pecking order considerations often dominate. Similarly, Frank & Goyal (2009) identified key factors influencing capital structure, such as profitability, firm size, and market-to-book ratio, emphasizing their consistent impact in U.S. firms. Expanding this perspective globally, Öztekin (2015) examined cross-country differences, highlighting how institutional factors like investor protection and market development shape capital structure decisions. Furthermore, studies like Graham (2000) quantified the magnitude of tax benefits and distress costs, revealing that many firms appear under-leveraged relative to theoretical predictions. Jensen & Meckling (2019) incorporated agency costs into the trade-off framework, highlighting conflicts between shareholders and managers or creditors. Debt can mitigate agency problems by reducing free cash flow, but excessive leverage may

exacerbate risk-shifting or underinvestment issues.

Critics argue that the trade-off theory oversimplifies the complexities of real-world decision-making. Myers (1984), along with Shyam-Sunder & Myers (1999) famously challenged the theory, proposing the pecking order theory as an alternative, which prioritizes internal financing over debt or equity issuance. While empirical evidence remains mixed, the trade-off theory provides a robust foundation for understanding capital structure decisions. Despite its limitations, the trade-off theory remains a valuable tool for understanding corporate finance decisions. Additionally, the theory has been adapted to address issues in emerging markets, where institutional differences affect the trade-off between debt and equity.

Several studies focus on the impact of government interventions. For instance, Agrawal & Matsa (2013) find that higher unemployment benefits lead to increased corporate leverage, particularly for labor-intensive and financially constrained firms. Keum & Meier (2024) discuss unemployment insurance reforms and their effect on the moral cost of layoffs, linking these changes to firms' leverage behaviors. Similarly, articles such as Xiong et al. (2021) examine infrastructure investments (e.g., high-speed rail) as a quasi-natural experiment to understand spatial dynamics and their influence on corporate financial behavior.

Graham, Leary, & Roberts (2015) provide a long-term perspective by analyzing the evolution of U.S. corporate capital structures over a century. They find that the general increase in leverage is driven by macroeconomic factors and the development of financial markets, suggesting that firms take on more debt as external conditions become favorable, reflecting an increased willingness to assume financial risk. Dang, Kim, & Shin (2014) focus on financial crises, demonstrating that firms are more inclined to increase leverage during such periods. This behavior reflects a heightened risk tolerance as companies adapt to external financing constraints, using debt to stabilize operations and sustain growth. Together, these studies with economic complexity highlight the interconnectedness of risk-taking behaviors, strategic decision-making, and external factors in shaping corporate capital structure decisions. Under an optimal capital structure, firms that are more risk-tolerant or inclined to take risks tend to adopt higher leverage, as they may be less apprehensive about potential risks, particularly when external conditions encourage or necessitate such behavior.

Recent studies have integrated behavioral insights, such as managerial overconfidence, into the trade-off theory. Research shows that managerial behavior significantly influences firms' capital structure decisions, particularly in their willingness to take on more leverage. Graham, Harvey & Puri (2013) showed that

managerial biases often lead to deviations from optimal leverage levels. Barberis & Thaler (2003) highlights that cognitive biases like overconfidence lead managers to underestimate risks, fostering riskier financial decisions. Baker & Wurgler (2002) demonstrate how optimistic managers exploit favorable market conditions to increase leverage, reflecting a risk-taking mindset. Similarly, Heaton (2002) argues that managerial optimism about future cash flows drives firms to adopt higher debt levels. These behavioral tendencies align with broader findings in the literature, emphasizing that risk-taking firms are more inclined to use leverage as a strategic tool to support growth and competitiveness. Therefore, the literature mentioned above highlights the various factors that influence capital structure decisions.

2.2 Recreational Marijuana Laws (RMLs)

Many entrepreneurs and prominent figures in the United States have openly admitted to using cannabis or supporting the legalization of recreational cannabis. These include Apple co-founder Steve Jobs, OpenAI CEO Sam Altman, former Google CEO Eric Schmidt, PayPal co-founder Peter Thiel, Tesla and SpaceX founder Elon Musk, Microsoft co-founder Bill Gates, Olympic swimmer Michael Phelps, 44th U.S. President Barack Obama, renowned rapper Snoop Dogg, and pop icon Madonna.

Reports suggest that Bill Gates experimented with cannabis during his youth. While he has been relatively low-key about his personal use, he has voiced support for cannabis legalization, particularly during the legislative process in Washington State. Since Colorado and Washington became the first states to legalize recreational cannabis in 2012, the topic has sparked widespread debate and controversy across the United States. Proponents argue that legalization generates economic benefits and reduces the burden on the criminal justice system. Opponents, however, raise concerns about potential health risks and social impacts, such as an increased risk of mental health disorders among young people. Despite the ongoing debate, cannabis legalization remains a contentious and complex social issue in the U.S.

Marijuana laws vary across different states in the United States. In some states, marijuana is completely illegal. Others have passed Medical Marijuana Laws (MMLs), allowing residents to obtain marijuana for medical purposes with a prescription from a physician. Additionally, some states have adopted a more lenient approach toward marijuana possession by passing Recreational Marijuana Laws (RMLs). Regulations regarding recreational marijuana laws vary across states. Within a general framework, individuals aged 21 and older are permitted to possess, use, and supply small amounts of marijuana for recreational purposes. For example, Colorado is the first state in the U.S. to legalize recreational marijuana. On November 6, 2012, voters approved

Amendment 64 to the Colorado State Constitution, and marijuana sales were fully legalized starting January 1, 2014 (Leung et al., 2019). Residents aged 21 or older can purchase up to 1 ounce (28 grams) of marijuana, while non-residents are limited to 0.25 ounces (7 grams). In California, adults aged 21 and older are legally allowed to possess, purchase, or gift up to 1 ounce (28 grams) of marijuana and up to 8 grams of concentrated cannabis. Adults can also grow up to six living marijuana plants for personal use. The legal status of recreational marijuana is illustrated in [Figure 1](#) and [Table 1](#).

[Insert [Figure 1](#) and [Table 1](#)]

The legalization of recreational cannabis has become a significant policy issue in recent years. Relevant studies have shown its notable impact on cannabis usage rates and social structures. Kephart et al. (2024) analyze the geographic distribution of recreational cannabis retailers and find that the increase in retailers is closely related to higher usage rates in disadvantaged communities, potentially exacerbating social inequality. Additionally, Bleyer et al. (2024) report that cannabis usage rates among adolescents significantly increase in states where recreational cannabis is legalized, linking this trend to the ongoing overdose crisis.

Hall & Lynskey (2020) suggested that the legalization of recreational cannabis in the United States has significantly lowered its price, enhanced its potency, increased its accessibility to adults, and led to more frequent use among adult users. Their findings underscore how market dynamics and legal frameworks influence consumption behaviors. Furthermore, Cerdá et al. (2020) found that among respondents aged 26 years or older, past-month marijuana use increased from 5.65% to 7.10%, while past-month frequent use rose from 2.13% to 2.62% following the enactment of RMLs. These findings highlight the demographic shifts in usage patterns post-legalization.

Liu, Xie & Chen (2025) investigated the impact of cannabis legalization on illicit drug markets and mortality rates. Their findings confirmed a marked increase in cannabis usage following legalization, potentially driving the expansion of darknet trading activities. Similarly, Boustead, Reicher & Goldrosen (2024) analyzed public safety and crime rates, highlighting a positive correlation between legalization and rising cannabis usage rates, further emphasizing the behavioral impacts of legal reforms.

Several studies also examined the influence of recreational cannabis policies on the use of other substances. Chen, Hsieh & Lin (2023) find that the increasing prevalence of marijuana usage and its adverse effects on inventors' health are two potential factors that may impede individual innovation. Asare, Westmaas & Nargis

(2024) noted that cannabis legalization not only boosted its usage rates but also affected the consumption patterns of cigarettes and other substances. Furthermore, Cullen et al. (2024) observed that cannabis accessibility during the COVID-19 pandemic further increased usage rates, particularly during lockdowns.

Lewis (2024) synthesized past and current policy analyses, stressing the need for health-centered drug policies to address the rising cannabis usage rates and related social issues following legalization. Finally, Dawson et al. (2024) demonstrated that states without recreational cannabis legalization exhibited lower usage rates of Δ -8-tetrahydrocannabinol (Δ 8-THC), whereas legalized states experienced significantly higher rates, supporting the notion that policy changes influence usage behaviors.⁴

2.3 Hypothesis development

Numerous studies have highlighted the detrimental effects of marijuana use. Research has linked marijuana consumption to various adverse physical consequences, including chronic bronchitis (Tashkin et al., 2002), addiction (Lopez-Quintero et al., 2011), lung cancer, and an elevated likelihood of transitioning to other substance use (Volkow et al., 2014). Additionally, marijuana use can contribute to decreased productivity due to the strong correlation between health and job performance (Arora, 2001; Goetzel et al., 2003; Loeppke et al., 2009). For instance, individuals who use marijuana may spend more time visiting doctors or struggle to maintain focus at work. As a result, marijuana use can indirectly undermine an individual's work performance by adversely affecting their physical health.

Research has established a connection between marijuana use and mental health disorders such as anxiety, depression, and schizophrenia. For example, Patten et al. (2002) find that adolescents who use marijuana weekly or more frequently face a two-fold increase in the risk of developing depression and anxiety later in life. Similarly, Hall (2006) demonstrate that marijuana use contributes to psychotic symptoms, citing a higher prevalence of such symptoms among younger individuals in developed countries following a rise in marijuana consumption. Furthermore, Arseneault et al. (2004) report that heavy marijuana use significantly increases the risk of developing schizophrenia later in life. Consequently, marijuana use may negatively affect an individual's productivity by deteriorating their mental health.

We are also concerned the effects of marijuana use on brain function, which can be significantly compromised. Quite a few studies have indicated that marijuana

⁴ Its psychoactive effects resemble those of Δ -9-tetrahydrocannabinol (Δ 9-THC), the chief psychoactive component in cannabis (Livne et al., 2022).

consumption may impair cognitive abilities (Curran et al., 2002; Hatchard et al., 2014; Lahanas & Cservenka, 2019). For instance, Hatchard et al. (2014) discover that the neural activity of younger adults who regularly use marijuana differ markedly from that of non-users, suggesting that marijuana use may have long-lasting adverse effects on executive functioning. Additionally, persistent marijuana use has been linked to a more pronounced decline in cognitive function over time (Meier et al., 2012). Recent users, compared to past users and non-users, exhibit greater deficits in areas such as overall cognitive performance, working memory, information processing speed, and executive functioning (Bolla et al., 2002; Thames et al., 2014). For example, marijuana use has been associated with impaired cognitive flexibility, which hinders the ability to adapt and make decisions in response to changing circumstances (Lahanas & Cservenka, 2019). Research also highlights that $\Delta 9$ -THC, the primary psychoactive compound in marijuana, negatively impacts episodic memory and learning (Curran et al., 2002). Moreover, heavy marijuana users demonstrate more severe impairments in attention and executive functioning compared to light users, even when accounting for other influencing factors (Bolla et al., 2002).

We primarily focus on the impact of marijuana use on behavioral decision-making, as changes in brain activity may directly or indirectly lead to behavioral impairments. Several studies have identified deficits in decision-making among adult marijuana users. For instance, research suggests that adults who frequently use marijuana demonstrate impaired decision-making during a card sorting task compared to those who use it infrequently (Pope & Yurgelun-Todd, 1996). Additionally, heavy marijuana users exhibit difficulties on the Iowa Gambling Task (IGT)⁵, both after short-term and prolonged abstinence (Bolla et al., 2002, 2005; Wesley et al., 2011; Whitlow et al., 2004). Performance on a specific type of impulsive behavior (i.e., poorer decision making) is associated with more cannabis use disorder symptoms (Gonzalez et al., 2012). Even more concerning, marijuana users may also exhibit an optimism bias. To illustrate, Wickens et al. (2019) find that when studying the driving behavior of marijuana users, they show a more optimistic bias and believed that they are less likely to crash under the influence of marijuana than others. Aloï et al. (2021) find that people with higher levels of cannabis use have reduced responsiveness when processing high-intensity potential future positive and negative events, and this may impair decision-making where future significant consequences.

⁵ The Iowa Gambling Task (IGT) is a decision-making assessment tool commonly used in psychology and neuroscience research, developed by Bechara et al. (1994). It is designed to evaluate individuals' decision-making abilities under conditions of uncertainty and risk, with a particular focus on patients with damage to the prefrontal cortex, especially the ventromedial prefrontal cortex (VMPFC).

All these studies demonstrate that marijuana consumption adversely impacts cognitive functions, mental well-being, and overall physical health. These impacts are likely to make it more challenging for executives to make sound decisions or may lead them to be more risk-taking in their business endeavors. Based on these surveys, the proportion of people consuming marijuana increases after state governments pass RMLs. This trend is not limited to low-income individuals; many high-level executives, managers, and board members also partake.

Consequently, we suspect that following the legalization of RMLs, there may be two situations. First, this trend is not limited to low-income individuals; high-level executives⁶, managers, and board members also use marijuana. More notably, entire management teams, finance and accounting departments, and even board directors within companies may engage in its use. The effects of marijuana could potentially influence their cognitive biases, ultimately leading them to make riskier, more reckless, or less efficient decisions. Second, based on the home bias, residents of this place are more likely to invest in companies in this area. If the residents of an area become more optimistic because of the marijuana use, their risk aversion will be reduced, so of course it will encourage companies to borrow more in their capital structure. In fact, we examine the impact of marijuana legalization on corporate leverage and develop several testable hypotheses as follows:

H1: *Compared to firms headquartered in states that have not passed RMLs, those in states with RMLs possess higher leverage.*

We also believe that the passage of RMLs in various states can influence firms to adopt higher financial leverage through multiple channels. Based on this, we propose the following predictions. First, prior studies document strong behavioral links between tobacco and marijuana use because tobacco users are more likely to also consume marijuana (Agrawal & Lynskey, 2009; Ramo et al., 2012). States with lower tobacco taxes tend to have higher smoking rates (Chaloupka & Warner, 2000), indicating a larger base of potential cannabis consumers post-legalization. Thus, RMLs may generate stronger demand shocks in these states, prompting firms to raise more external

⁶ Several high-level executives have publicly supported marijuana legalization, with many admitting past use. Notable figures include Elon Musk (CEO of Tesla and SpaceX), who smoked marijuana during a live podcast interview; Mark Johnson (former CEO of Zite), who openly discussed his regular use of cannabis in the tech industry; Michael Bloomberg (founder of Bloomberg L.P. and former Mayor of New York City), who admitted, "You bet I did. And I enjoyed it."; Richard Branson (founder of Virgin Group), a vocal advocate for legalization; John Mackey (co-founder of Whole Foods Market), who has expressed support for decriminalization; and George Zimmer (founder and former CEO of Men's Wearhouse), who has publicly endorsed cannabis use. Additionally, Bill Gates (co-founder of Microsoft) confirmed in a 2012 interview with BuzzFeed that he voted "yes" on Washington state's marijuana legalization referendum. (Sources: *The Guardian*, *Business Insider*, *Fortune*, *BuzzFeed News*).

capital to capture new opportunities. Moreover, low-tax states may reflect more permissive or business-friendly regulatory environments, lowering perceived policy risk and encouraging greater leverage (Myers, 1977; Graham, 2003). Therefore, we make the following prediction.

H2a: *Compared to firms headquartered in states without RMLs, those in states with RMLs tend to adopt higher financial leverage, particularly in states with lower tobacco taxes.*

Second, technology firms traditionally maintain low financial leverage due to their reliance on intangible assets, such as intellectual property and R&D, which are difficult to collateralize. They also face greater information asymmetry and more volatile cash flows; accordingly, debt financing is relatively costly or inaccessible to these technology firms (Myers & Majluf, 1984; Hall, 2002). As a result, they tend to adopt more conservative capital structures compared to asset-heavy industries (Frank & Goyal, 2009). Therefore, it is reasonable to infer that technology firms have more room to increase leverage in states that enact RMLs than firms in traditional industries. Hence, we expect the following outcome.

H2b: *Compared to firms headquartered in states without RMLs, those in states with RMLs tend to adopt higher financial leverage, especially for technology firms.*

Last, excessive borrowing can constrain a firm's capacity to provide competitive executive compensation, primarily because debt servicing obligations reduce the availability of internal funds. This tension between leverage and compensation becomes particularly salient when executives are highly paid, as they tend to be more sensitive to financial distress that may diminish the value of their compensation packages (Jensen, 1986; Edmans et al., 2009). Empirical studies have shown that executives with significant compensation tied to firm performance or deferred payments, such as pensions or inside debt, often adopt more conservative financial policies to protect their claims (Sundaram & Yermack, 2007). In contrast, executives with relatively lower salaries may have limited incentive to resist increases in leverage. This tendency may become more pronounced in states that have enacted RMLs, which are associated with broader changes in firm behavior and local economic conditions. Thus, we arrive at the following prediction.

H2c: *Compared to firms headquartered in states without RMLs, those in states with RMLs are more likely to borrow more, especially when they have lower executive salaries.*

Finally, we posit the effect of marijuana use on firm's operating performance.

Existing literature suggests that cognitive biases, such as overconfidence, can lead managers to underestimate risk and make excessively risky financial decisions (Malmendier & Tate, 2005). According to the theory of optimal capital structure, firms with a higher risk appetite tend to adopt higher leverage ratios (Myers, 1984). While debt provides tax advantages, excessive leverage also increases the likelihood of financial distress and potential bankruptcy (Kraus & Litzenberger, 1973). Moreover, if firms raise their debt levels due to changes in managerial incentives, yet fail to improve investment efficiency or revenue performance, they may face deteriorating profitability over time (Jensen & Meckling, 2019). Of particular concern, the risk-taking behavior associated with RMLs may not lead to productive innovation or sustainable growth. Firms that assume higher leverage due to altered optimistic risk preferences of managers and shareholders may misallocate capital, pursue speculative projects, or lose operational efficiency (Baker & Wurgler, 2002; Barberis & Thaler, 2003; Graham et al., 2013). Based on these considerations, we argue that firms under the influence of cognitive biases and misaligned managerial and shareholder incentives are likely to deviate from optimal financial decision-making. Accordingly, we propose the following prediction.

H3: *Compared to firms headquartered in states without RMLs, those in states with RMLs are unable to achieve better operating performance.*

3. Data and Methodology

3.1 Data

Our sample consists of U.S. listed firms covered in Compustat and CRSP databases between 2007 and 2022, five years before the first enactments of a state-level laws allowing recreational marijuana use by Colorado and Washington in 2012. Besides, we use the historical location data from Augmented 10-X Header dataset to correct the location. Our final sample consists of 57,919 firm-year observations from 2007 to 2022, including specific 6,938 firms.

Following Frank and Goyal (2009), we primarily use the total debt to assets ratio (TDA)⁷ to measure firm leverage. The Bureau of Economic Analysis provides data on state GDP; the US Census Bureau provides data on state population; and the US Bureau

⁷ We also follow Frank & Goyal (2009) to test the long-term debt to assets ratio (LDA), the total debt to market value of assets ratio (TDM) and the long-term debt to market value of assets ratio (LDM). However, previous studies have indicated that an overreliance on market value may lead to the risk of overlooking a firm's intrinsic value (Baker & Wurgler, 2002). Therefore, this study adopts the book value approach to measure assets.

of Labor Statistics provides data on state unemployment rates. We also obtain data on CEO compensation from ExecuComp and completed M&A transactions⁸ from the Thomson One Banker Securities Data Company (SDC) database.

The detailed definitions of the variables are available in [Appendix A. Table 2 Panel A](#) displays the summary statistics. After winsorized the leverage measures at level 1% and 99% levels for each year, we have the average (median) *TDA* in our sample is 0.222 (0.161). In addition, the average (median) size of the firms in our sample is \$6.649 billion (\$6.674 billion) with a market-to-book ratio of 0.122 (0.021). [Table 2 Panel B](#) displays the correlation matrix of the variables used in the baseline regression in our paper. Our leverage proxies, *TDA*, are significantly positively correlated with *RML*.

[Insert [Table 2](#)]

3.2 Methodology

In this section, we exploit the variations in firms' leverage in the staggered implementation of RMLs across states.

$$Leverage_{i,t+1} = \alpha + \beta RML_{i,t} + \sum_j \gamma_j Controls_{i,j,t} + \lambda_i + \delta_t + \epsilon_{i,t} \quad (1)$$

where $Leverage_{i,t+1}$ is firm i 's total debt to assets ratio in year t . Our key explanatory variable, *RML*, is an interaction term equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. The control variables are firm-level and state-level factors potentially related to firm risk. In our baseline regression, we control for firm-level variables that may affect firms' leverage such as market-to-book ratio (*Mktbk*), industry leverage (*IndustLev*), *Tangibility*, *Profit*, *Assets*, firm age (*FirmAge*) and *Labor*. Additionally, we control for various macroeconomic factors, including state-level population (*Population*), taxation (*Tax*), GDP growth rate (*GDPgrowthrate*), and unemployment rate (*Unemployment*). $\epsilon_{i,t}$ is the error term. Coefficient β measures the effect of $RML_{i,t}$ on $Leverage_{i,t+1}$ in [Eq. \(1\)](#). To help rule out time-varying heterogeneity and control for time-invariant characteristics across firms, the specification also include both year fixed effects and firm fixed effects. Standard errors are clustered at firm level.

We follow prior studies (e.g., Serfling, 2016; Bai et al., 2020) to adopt propensity-score-matched (PSM) to further assuage endogeneity concerns. We construct a PSM sample by matching the control and treatment firms in year t based on industry and all

⁸ The selection criteria for completed M&A transactions follow the methodology outlined in Li et al. (2018).

control variables in [Eq.\(1\)](#). The treatment group consists of firms located in states that pass RMLs in year t . The control group consists of firms located in states that had not yet enacted RMLs by year t .

To ensure robustness, we employ multiple matching techniques beyond standard propensity score matching. First, we use radius matching, which selects control firms within a predefined caliper (0.05) of the propensity score to ensure similarity between treated and matched control firms (Dehejia & Wahba, 2002). Second, we apply nearest neighbor matching, which pairs each treated firm with the most similar untreated firm based on propensity scores (Abadie & Imbens, 2011). Third, we implement coarsened exact matching (CEM), a method that reduces imbalance by temporarily coarsening continuous variables before matching, thus improving covariate balance (Iacus et al., 2012). Fourth, we also employ entropy balance matching, which reweights the control group to achieve covariate balance by exactly matching the first moments (Hainmueller, 2012).

Last but not least, we estimate a Cox proportional hazards model in which the event is a state's first adoption of an RMLs and the unit of observation is the state-year. We include a set of macroeconomic and social covariates: GDP and GDP growth (BEA), unemployment (BLS/LAUS), crime (FBI), and CO₂ emissions (EIA) along with year fixed effects. As shown in [Table 3](#), the estimated coefficients on these covariates are not statistically distinguishable from zero, suggesting that the hazard of RMLs adoption is not systematically higher in states experience stronger macroeconomic performance, labor market changes, or shifts in crime and emissions. These results are consistent with the view that RMLs adoption timing is not primarily driven by the observed macroeconomic and social factors considered here, alleviating concerns that our main estimates are confounded by these pre-existing trends.

By employing these matching techniques, we further mitigate concerns related to selection bias and omitted variable bias, thereby increasing the robustness and credibility of our results.

4. Main Results

4.1 Baseline Results

[Table 4](#) presents the difference-in-differences estimates of the impact of RMLs on firms' leverage with propensity-score matching (PSM) methods. As shown in [Eq. \(1\)](#), the coefficient of interest, β , remains consistently positive and statistically significant across all columns.

[Insert [Table 4](#)]

The results indicate that RMLs has a significant positive effect on leverage across all models. Specifically, in [Table 4](#) the regression with dependent variable *TDA* (Models 1 and 2) show that the coefficients of *RML* are 0.02 ($t = 2.72$) and 0.017 ($t = 2.30$), respectively. These results are statistically significant at the 1% and 5% level, respectively, suggesting that firms tend to increase their debt financing following the passage of RMLs, leading to higher leverage ratios.

Notably, the control variables align with existing literature: Industry leverage is significantly positive, indicating that firms in industries with higher leverage tend to maintain higher debt ratios. Firm size is also positively associated with leverage, suggesting that larger firms generally employ more debt financing. Market-to-book ratio has a significant negative effect on leverage, consistent with the notion that high-growth firms rely less on debt financing. Profitability is also negatively associated with leverage, supporting the pecking order theory, which suggests that more profitable firms prefer internal financing over debt.

In the internet appendix we also use the radius matching, nearest neighbor matching, coarsened exact matching and entropy matching methods. As shown in [IA1](#), our results remain consistent regardless of the matching method used. The coefficients of *RML* are all positive and statistically significant. In [IA5](#), we further test the Actual Buyback Ratio to ensure that firms are truly increasing leverage rather than adjusting their capital structure by reducing assets. In [IA6](#), we additionally include firms in the finance and utilities industries, and the results remain robust.

Overall, these findings indicate a significant relationship between RMLs passage and increased corporate leverage. This may reflect firms' adjustments in capital structure in response to changes in the regulatory environment or expectations of future market opportunities following marijuana legalization.

4.2 Estimation of Staggered Difference-in-Differences Framework

To address concerns associated with staggered treatment timing in difference-in-differences (DiD) designs, we implement the stacked DiD approach proposed by Cengiz et al. (2019) and the DiD imputation estimator developed by Borusyak, Jaravel, & Spiess (2024)⁹. These methods provide more credible causal estimates by avoiding

⁹ While the group-time ATT estimator by Callaway and Sant'Anna (2021) is widely used, it is not without limitations. Roth et al. (2023) caution that the method may be unstable when there are few treated cohorts or heterogeneous pre-trends. Athey & Imbens (2022) also emphasize its sensitivity to treatment spillovers and violations of the parallel trend assumption. In contrast, imputation-based approaches such as Borusyak et al. (2024) offer more efficient and robust estimates, especially in large panels and settings with treatment effect heterogeneity.

biases introduced by negative weighting and inappropriate control groups that can arise in traditional two-way fixed effects (TWFE) models under treatment effect heterogeneity (Goodman-Bacon, 2021).

Additionally, in [Figure 2](#) and [Figure 3](#) we verify the pre-trend assumption, confirming that firms in treated and control groups exhibit parallel trends before the passage of RMLs. These robustness checks strengthen the validity of the estimated impact of RMLs on corporate leverage.

[Insert [Figure 2](#) and [Figure 3](#)]

Overall, these findings indicate a significant relationship between RMLs passage and increased corporate leverage. This may reflect firms' adjustments in capital structure in response to changes in the regulatory environment or expectations of future market opportunities following marijuana legalization.

5. Additional Tests

To further investigate the mechanisms through which the passage of RMLs influences corporate leverage, we conduct additional tests focusing on three potential channels: tobacco tax rates, technology firms and executive compensations. Additionally, we extend our analysis to merger and acquisition activity, return volatility, operating performance and accident mortality deaths. These analyses provide deeper insights into how different firm characteristics interact with the regulatory changes induced by RMLs.

5.1 Potential Channels

5.1.1 Tobacco Tax

Prior research has identified strong behavioral and epidemiological linkages between tobacco and marijuana use. Numerous medical studies show that tobacco users are significantly more likely to consume marijuana as well (Agrawal & Lynskey, 2009; Ramo et al., 2012). Moreover, states with lower tobacco taxes generally exhibit higher smoking rates (Chaloupka & Warner, 2000), suggesting a larger pool of potential marijuana users following legalization. This implies that in low tobacco tax states, RMLs may lead to a larger expansion of consumer demand for cannabis products. Firms headquartered in these states may experience a stronger impact from marijuana and face higher incentives to raise outside capital to seize these emerging opportunities. Additionally, a lower-tax policy environment may also signal a more business-friendly or permissive regulatory stance in general, reducing perceived policy risk and increasing the willingness of lenders to extend credit to firms operating in such regions

(Myers, 1977; Graham, 2003).

[Insert [Table 5](#)]

[Table 5](#) presents the regression results analyzing the impact of RMLs on firm leverage, categorized by tobacco tax levels. Specifically, for firms in low tobacco tax regions (Models 1 and 3), the coefficients of *RML* are 0.028 ($t = 2.67$) and 0.025 ($t = 2.28$). In contrast, for firms in high tobacco tax regions (Models 2 and 4), the coefficients of *RML* are 0.017 ($t = 1.62$) and 0.012 ($t = 1.24$). The coefficients for firms in low tobacco tax regions are consistently larger than those for firms in high tobacco tax regions. These results indicate that firms in states with lower tobacco taxes experience a more pronounced and statistically significant increase in leverage following the passage of RMLs. This finding supports the notion that marijuana and tobacco are complementary goods. In states with low tobacco taxes, the passage of RMLs may further stimulate marijuana consumption among existing tobacco users, thereby indirectly driving up corporate borrowing (Agrawal & Lynskey, 2009; Ramo et al., 2012; Schauer et al., 2015).

5.1.2 Technology Firms

Technology firms are traditionally characterized by low financial leverage. This is primarily due to their high reliance on intangible assets, such as intellectual property and R&D, which are difficult to collateralize. In addition, these firms tend to face high information asymmetry and volatile cash flows, which makes debt financing more costly or less accessible (Myers & Majluf, 1984; Hall, 2002). As a result, high-tech firms are often more conservative in their use of debt compared to firms in traditional asset-heavy industries (Frank & Goyal, 2009). RMLs can serve as a signal of regulatory relaxation for high-tech firms, which are typically more sensitive to institutional and policy uncertainty, firms' manager or shareholder may be affected by the marijuana use and encouraged bolder financial decisions.

[Insert [Table 6](#)]

[Table 6](#) presents the regression results examining the effect of RMLs on firm leverage, distinguishing between firms with technology firms or not¹⁰. Specifically, for non-tech firms (Models 1 and 3), the coefficients of *RML* are 0.014 ($t = 1.77$) and 0.011 ($t = 1.43$). Conversely, for high-tech firms (Models 2 and 4), the coefficients of *RML* are 0.045 ($t = 2.73$) and 0.042 ($t = 2.55$), we also make the Wald test, the coefficients are higher and more significant than results of non-tech firms.

¹⁰ Whether a firm is classified as a technology firm is defined by Loughran & Ritter (2004).

These results indicate that technology firms experience a more pronounced increase in leverage following the passage of revised managerial liability laws. This suggests that firms in the technology sector, which are typically characterized by lower initial leverage ratios, have greater capacity to raise leverage when they are located in states that enact such laws. In contrast, firms in traditional industries, where leverage ratios are already relatively high (for example, 60 percent or 70 percent), may have less room to further increase their leverage even if they are subject to the same legal changes.

5.1.3 Executive Compensations

Excessive borrowing can constrain a firm's ability to offer competitive executive salaries, as debt repayment obligations limit available funds for compensation. Additionally, highly paid executives may resist increasing leverage due to concerns about financial distress, which could ultimately impact their compensation (Jensen, 1986; Sundaram & Yermack, 2007; Edmans et al., 2009). To assess the role of executive compensation in shaping firms' borrowing behavior post-RML, we segment firms based on high and low executive salaries.

[Insert [Table 7](#)]

[Table 7](#) presents the regression results examining the impact of RMLs on firm leverage, distinguishing firms based on executive compensation levels. Specifically, for firms with low executive salaries (Models 1 and 3), the coefficients of *RML* are 0.028 ($t = 2.16$) and 0.027 ($t = 2.17$), with statistically significant at the 5% level. In contrast, for firms with high executive salaries (Models 2 and 4), the coefficients of *RML* are 0.012 ($t = 1.09$) and 0.011 ($t = 1.02$), neither of which is statistically significant. The results reveal that firms with lower executive salaries are more likely to increase their borrowing after the passage of RMLs, suggesting that financial constraints in executive compensation may drive leverage decisions and potentially indicating differences in risk preferences or financial constraints across compensation levels.

5.2 Merger and Acquisition (M&A) Activity

[Table 8](#) presents the regression analysis M&A activity using propensity-score matching. The dependent variable is *MAevents* and *DealValue*. *MAevents* represents the actual number of M&A transactions a firm will undertake in the next year. *DealValue* is the total value of consideration paid by the acquiror, excluding fees and expenses.

The analysis presented in [Table 8](#) reveals that firms complying with RMLs do not exhibit a statistically significant change in their M&A activities post-compliance. Specifically, for *MAevents* (Models 1 and 2), the coefficients of *RML* are both -0.010 ($t = -1.17$ and $t = -1.16$) and for *DealValue* (Models 5 and 6), the coefficients of *RML* are

21.434 ($t = 1.01$) and 22.394 ($t = 1.08$). The coefficients associated with *RML* across various models are negligible and lack statistical significance, indicating that regulatory compliance does not substantially influence a firm's propensity to engage in M&A transactions.

[Insert [Table 8](#)]

Notably, the interaction term $RML \times TDA$ is negative but not statistically significant across all models, suggesting that firms do not engage in more M&A activity by increasing leverage following the passage of RMLs.

This outcome suggests that factors beyond regulatory compliance play a more pivotal role in driving M&A activities. Empirical studies have identified several determinants influencing M&A decisions. For instance, macroeconomic conditions, such as economic growth and interest rates, significantly impact M&A activity (Vasnetsov et al., 2023). Additionally, firm-specific characteristics, including size, financial resources, and international experience, are critical determinants of successful M&A endeavors (Zhou et al., 2024). Industry-level factors, such as technological intensity and market competition, also play a substantial role in shaping M&A strategies (Erel et al., 2012).

Furthermore, cross-border M&A activities are influenced by factors like cultural differences, exchange rates, and political stability, which can either facilitate or hinder such transactions (Erel et al., 2012). These findings underscore that while regulatory compliance is crucial, M&A activities are shaped by a wide range of additional factors beyond regulatory considerations.

In summary, the absence of a significant change in M&A activities following RMLs compliance suggests that firms' merger and acquisition decisions are more heavily influenced by a complex array of factors beyond regulatory adherence.

5.3 Return Volatility

Our results presented in [Table 9](#) indicate that firms passing RMLs do not experience a statistically significant change in return volatility (*RetVol*) or its logarithmic transformation (*LogRetVol*). In particular, for *RetVol* (Models 1 and 2), the coefficients of *RML* are 0.009 ($t = 0.38$) and 0.011 ($t = 0.50$), respectively. Likewise, for *LogRetVol* (Models 5 and 6), the coefficients of *RML* are 0.008 ($t = 0.34$) and 0.011 ($t = 0.47$). The coefficients of *RML* are small and statistically insignificant across all models, suggesting that the passage of RMLs does not have a meaningful impact on return volatility, regulatory adherence does not meaningfully alter stock return volatility.

[Insert [Table 9](#)]

Interestingly, the interaction term $RML \times TDA$ is positive but not statistically significant across all models, suggesting that firms' return volatility does not increase through higher leverage following the passage of RMLs.

This finding contrasts with high-profile events where firm-specific shocks have led to significant market reactions. For example, when Elon Musk was seen smoking marijuana on a podcast, Tesla's stock experienced a sharp decline and increased volatility the following day. However, such fluctuations are likely driven by idiosyncratic factors, including investor sentiment and media coverage, rather than fundamental changes in firm risk characteristics. Similarly, in our study, the lack of significant changes in return volatility after passing RMLs suggests that other market forces and firm-specific events may have a more dominant role in influencing stock volatility than regulatory compliance alone.

From another perspective, our findings are consistent with the theoretical offsetting effects, which suggest that the enactment of RMLs influences return volatility through two opposing mechanisms. On the one hand, Chen et al. (2023) document that RMLs lead to a decline in innovation and R&D investment, which is expected to reduce return volatility by diminishing firms' exposure to uncertain growth opportunities and technological risks. On the other hand, our results indicate that RMLs adoption is associated with a significant increase in leverage, which, in turn, is typically linked to heightened return volatility due to greater financial risk and amplified sensitivity to market fluctuations. The interaction between these two opposing forces, the volatility-reducing effect of lower innovation and the volatility-increasing effect of higher leverage, suggests a potential equilibrium where the overall impact on return volatility remains insignificant. This theoretical offset provides a plausible explanation for our empirical finding that the passage of RMLs does not result in a statistically significant change in stock return volatility.

5.4 Operating Performance

The three identified channels—states have lower tobacco tax, technology firms and lower executive compensation suggesting that the increase in leverage following the passage of RMLs is not necessarily a rational optimization of capital structure but rather a behavioral response. Technology firms increase their borrowing due to regulatory relaxation, firms in low-tobacco-tax states respond to shifting consumer demand, and companies with lower executive salaries take on more debt. However, if these leverage increases are not made under rational expectations but instead result from behavioral factors or managerial biases, they may lead firms away from their

optimal capital structure.

A deviation from equilibrium suggests that firms may encounter operational inefficiencies, ultimately weakening their financial performance. If the additional leverage acquired following the enactment of RMLs is not supported by corresponding productivity gains or growth opportunities, firms may face heightened financial distress, increased interest burdens, or inefficient resource allocation. To assess the real effects of this leverage increase, we examine its impact on firms' operating performance. In order to test this relationship, we replace $Leverage_{i,t+1}$ with $Operating\ Performance_{i,t+1}$ in [Eq.\(1\)](#). The regression equation is specified as follows:

$$Operating\ Performance_{i,t+1} = \alpha + \beta RML_{i,t} + \sum_j \gamma_j Controls_{i,j,t} + \lambda_i + \delta_t + \epsilon_{i,t} \quad (2)$$

where i indexes firms, t indexes years and $\epsilon_{i,t}$ is the error term. To evaluate the impact of RMLs on firm performance, we analyze key measures of operating efficiency, the change in net income between year (t) and year ($t-1$), divided by the average total assets over the two periods (*ROAchange*). Similarity, the specification also includes both year fixed effects and firm fixed effects. Standard errors are clustered by firm. The results presented in [Table 10](#) suggesting that firms are unable to achieve better operating performance following the passage of RMLs.

[Insert [Table 10](#)]

More precisely, the regression with dependent variable *ROAchange* (Models 1 and 2), the coefficients of *RML* are 0.006 ($t=0.59$) and 0.015 ($t=1.60$), respectively. This suggests that, following the implementation of RMLs, managers or shareholders did not take any notable actions that significantly influenced the firm, resulting in no substantial improvement in overall profitability.

Importantly, the negative and statistically significant interaction term $RML \times TDA$ across all models suggests that the increase in leverage following the enactment of RMLs does not translate into improved efficiency or growth. Instead, the behaviorally driven rise in borrowing may result in suboptimal capital allocation. Although firms in states that have passed RMLs take on higher leverage, the increased debt may not utilize for investments in positive NPV projects, thereby reducing firms' profitability. These results align with the perspective that firms do not fully adjust their financial decisions in a rational manner after RMLs adoption, thereby failing to generate a positive real impact on firms' operating performance.

5.5 Accident Mortality Deaths

The analysis presented in [Appendix B](#) indicates a statistically significant increase in accident mortality rates following the implementation of RML. In Model 1, the coefficient of *RML* is 71.262 ($t = 11.15$), statistically significant at the 1% level. In Model 2, the coefficient decreases to 62.186 ($t = 12.64$), but remains statistically significant at the 1% level. These findings suggest that the policy change is associated with a rise in accidental deaths. The coefficient implies that after the passage of RMLs the number of accident-related deaths per 100,000 people increased by 62.186 to 71.262.

This finding aligns with previous research examining the consequences of cannabis legalization. For instance, studies have reported increases in traffic fatalities following the legalization of recreational marijuana. Farmer, Monfort & Woods (2022) find that crash rates spiked in states like California, Colorado, Nevada, Oregon, and Washington after the legalization of recreational marijuana use and retail sales. Similarly, Kamer, Warshafsky, & Kamer (2020) indicated that the first four states to legalize recreational marijuana (Colorado, Washington, Oregon, and Alaska) experienced changes in traffic fatality rates post-legalization.

These studies suggest that the increase in accident mortality deaths may be attributed to factors such as impaired driving due to higher cannabis consumption following legalization. The correlation between cannabis use and impaired motor skills is well-documented, leading to concerns about road safety in the context of legalization.

Briefly put, the observed rise in accident mortality deaths following the implementation of RMLs is consistent with existing literature that links cannabis legalization to an increase in accidental deaths, particularly those related to traffic incidents.

6. Conclusion

This study examines the impact of Recreational Marijuana Legalizations (RMLs) on financial leverage. Utilizing a staggered difference-in-differences approach, we find that firms located in states with RMLs experience a significant increase in leverage, suggesting that marijuana legalization influences corporate financial decision-making. The effect is more pronounced among technology firms, companies in states with lower tobacco taxes, and firms with lower executive compensation, indicating multiple channels through which RMLs shape corporate financing strategies.

Our analysis further reveals that no significant impact of RMLs on firms' mergers and acquisition activity, nor on stock return volatility. Both of the extended results indicate that while legalization affects corporate leverage, it does not disrupt overall market stability. Moreover, we find that while the increase in leverage does not translate

into enhanced firm performance, it is associated with a decline in operating performance. This suggests that although RMLs create new business opportunities, they also introduce financial risks and inefficiencies that may offset potential benefits.

Beyond corporate finance, our findings underscore the broader societal implications of RMLs. Specifically, we document a statistically significant increase in accident mortality deaths post-legalization, reinforcing concerns about the public safety risks associated with increased cannabis consumption. This highlights the need for policymakers to carefully balance economic considerations with potential social costs when implementing marijuana-related legislation.

Overall, this study adopts a health economics perspective, contributes to the growing literature on the intersection of social policies and corporate financial behavior. By linking marijuana legalization to firms' capital structure decisions and public safety outcomes, we provide new insights into the unintended economic and societal consequences of RMLs. Future research could explore the long-term implications of RMLs on managerial decision-making, industry-specific effects, executive overinvestment (or underinvestment) and the role of regulatory frameworks in mitigating associated risks.

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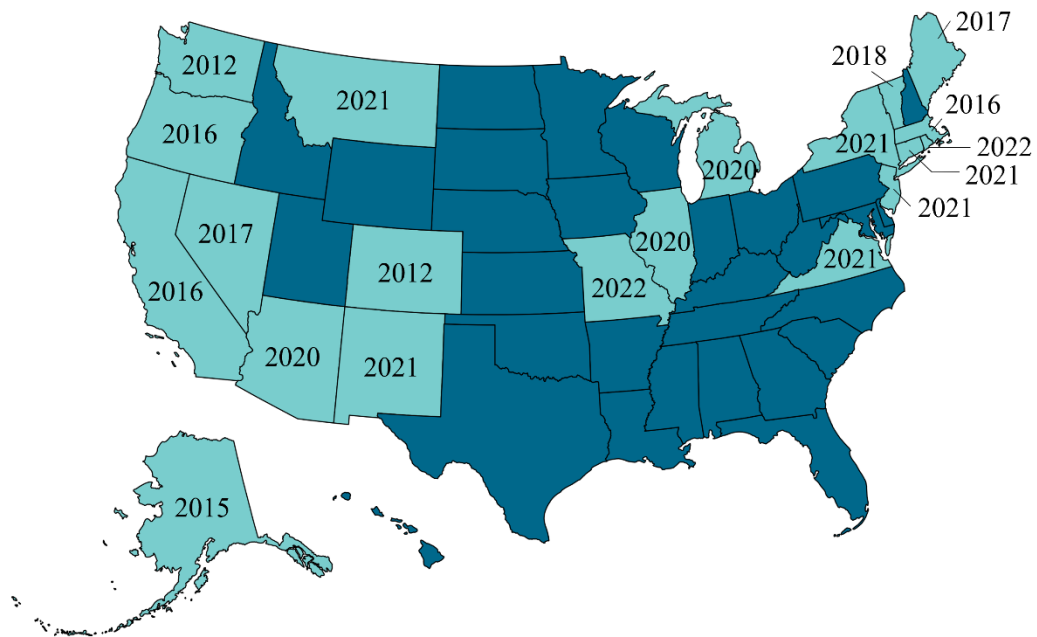
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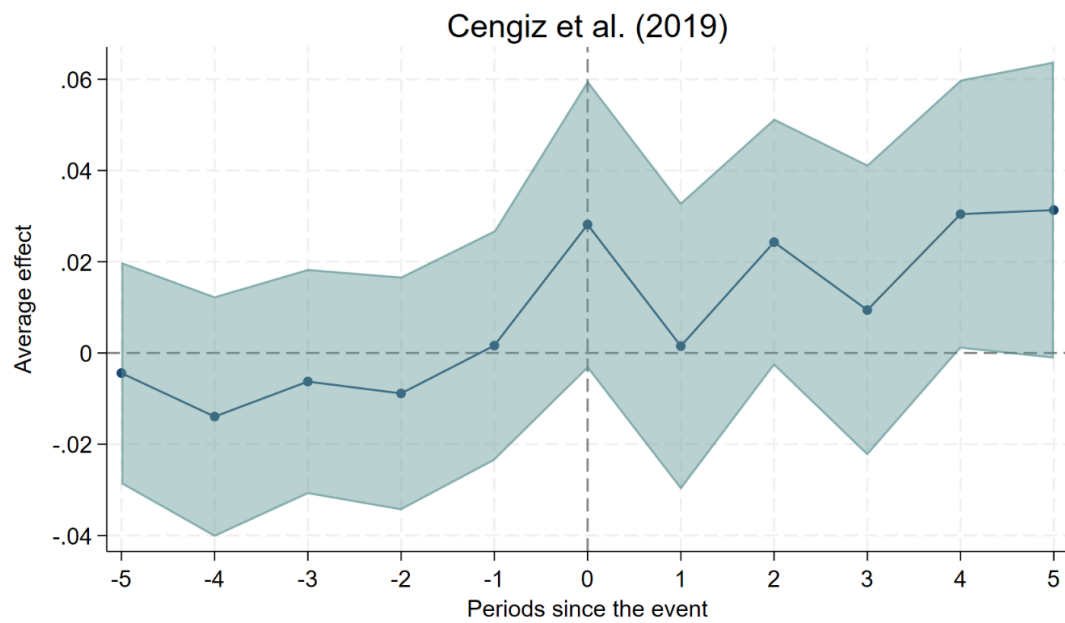
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Figure 1. State Recreational Marijuana Laws Passing



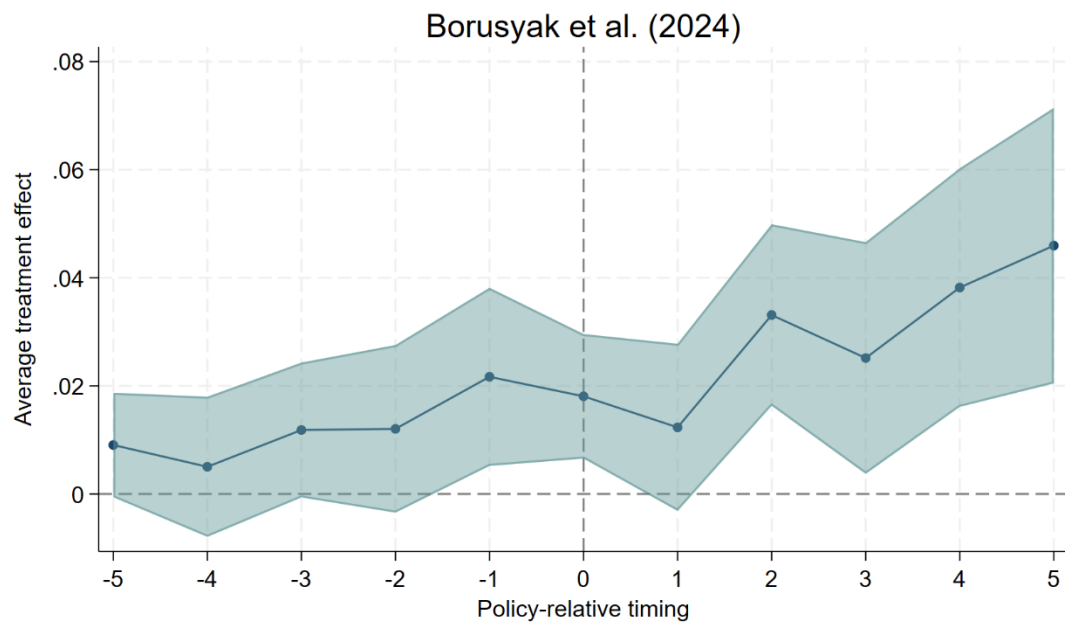
Notes: This figure displays the legislative landscape of states regarding RMLs before 2022. The turquoise areas in the figure indicate the states that have already legalized recreational marijuana, and the years they pass the RMLs are also noted.

Figure 2. Stacked Difference-in-Differences Analysis of Cengiz et al. (2019)



Notes: This figure reports stacked difference-in-differences (stacked DiD) event-study estimates following Cengiz et al. (2019). For each adoption cohort, we re-center time around the state's RMLs adoption year and stack cohorts to estimate dynamic treatment effects. Event time t is measured in years relative to adoption: $t=0$ is the adoption year, and $t \in \{-5, \dots, +5\}$ indicates years before and after adoption. The dots represent the estimated average effect at each event time, and the shaded region shows the 95% confidence interval. Standard errors are clustered at the state level.

Figure 3. DiD Imputation



Notes: This figure reports event-study estimates using the imputation-based difference-in-differences method of Borusyak et al. (2024). The estimator first imputes untreated potential outcomes for treated states by fitting an outcome model using never-treated and not-yet-treated observations, and then constructs cohort- and event-time-specific treatment effects which are aggregated into the overall dynamic profile. Event time t is measured in years relative to a state's RMLs adoption, where $t=0$ denotes the adoption year and $t \in \{-5, \dots, +5\}$ indexes years before and after adoption. The dots plot the estimated average treatment effect at each event time, and the shaded area shows the 95% confidence interval. Standard errors are clustered at the state level.

Table 1. The Implementation of RMLs in US States as of 2023

This table lists the effective year of the RMLs in US states.

State	RMLs	State	RMLs
Alabama		Montana	2021
Alaska	2015	Nebraska	
Arizona	2020	Nevada	2017
Arkansas		New Hampshire	
California	2016	New Jersey	2021
Colorado	2012	New Mexico	2021
Connecticut	2021	New York	2021
Delaware	2023	North Carolina	
Florida		North Dakota	
Georgia		Ohio	2023
Hawaii		Oklahoma	
Idaho		Oregon	2016
Illinois	2020	Pennsylvania	
Indiana		Rhode Island	2022
Iowa		South Carolina	
Kansas		South Dakota	2020
Kentucky		Tennessee	
Louisiana		Texas	
Maine	2017	Utah	
Maryland	2023	Vermont	2018
Massachusetts	2016	Virginia	2021
Michigan	2020	Washington	2012
Minnesota	2023	West Virginia	
Mississippi		Wisconsin	
Missouri	2022	Wyoming	

Table 2 Panel A. Summary Statistics

This table presents summary statistics of variables that have been used in the baseline regressions in our paper. *RML* is a dummy variable equal to one if a state has passed the Recreational Marijuana Laws (RMLs) and the observation falls in the post-treatment period, and zero otherwise. *RetVol* is the standard deviation of daily stock returns. *Log1RetVol* is $\log(1+RetVol)$. *TDA* is the ratio of total debt to assets. *ROAchange* is the change in ROA between year (*t*) and year (*t*−1), divided by the average total assets over the two periods. *EventYear* is a dummy variable that equal to one if RMLs were passed in the year and zero otherwise. *IndustLev* is the median of total debt to market value of assets by 2-digit SIC code and by year. *Mktbk* is the sum of the market value of equity divided by assets. *Tangibility* is the net property, plant, and equipment divided by assets. *Profit* is the operating income before depreciation divided by assets. *Assets* is the log of assets deflated to 1992 dollars using the GDP deflator. *FirmAge* is the number of years since being included in the Compustat database. *Labor* is the ratio of the number of employees to property, plant, and equipment. *Unemployment* is the unemployment rate collected from the Local Area Unemployment Statistics from the Bureau of Labor Statistics. *Population* is the state-level population collected from the US Census Bureau and Federal Reserve Economic Data. *GDPgrowthrate* is the rate of GDP in the year (*t*) and year (*t*−1), scaled by sales in the year (*t*−1). *Tax* is the state-level taxes on production and imports less subsidies collected from the US Bureau of Economic Analysis. *Production* is the industry-adjusted production and is defined as the sales divided by assets. *TDA* is winsorized at the 1st and 99th percentiles to tease out the outliers. Appendix A provides the definitions for all variables.

	Obs	Mean	SD	Q1	Q2	Q3
<i>RML</i>	57,919	0.172	0.377	0	0	0
<i>RetVol</i>	57,874	0.035	0.028	0.019	0.029	0.043
<i>Log1RetVol</i>	57,874	0.034	0.024	0.019	0.028	0.042
<i>TDA</i>	57,641	0.222	0.224	0.031	0.161	0.346
<i>ROAchange</i>	57,919	0.005	0.779	-0.024	0.001	0.025
<i>EventYear</i>	57,919	0.045	0.206	0	0	0
<i>IndustLev</i>	57,902	0.212	0.195	0.058	0.156	0.338
<i>Mktbk</i>	57,753	0.122	14.503	0.006	0.021	0.067
<i>Tangibility</i>	57,517	0.199	0.233	0.026	0.102	0.279
<i>Profit</i>	57,663	-0.009	0.503	0.007	0.07	0.135
<i>Assets</i>	57,894	6.649	2.21	5.104	6.674	8.099
<i>FirmAge</i>	57,919	13.475	7.896	6	14	19
<i>Labor</i>	57,919	0.021	0.194	0.001	0.007	0.017
<i>Unemployment</i>	57,919	6.174	2.384	4.3	5.5	7.8
<i>Population</i>	57,919	16.279	0.862	15.687	16.267	17.026
<i>GDPgrowthrate</i>	57,919	0.001	0.013	0	0.001	0.002
<i>Tax</i>	57,919	11.416	0.986	10.667	11.391	12.352

Table 2 Panel B. Correlation Matrix

The table shows the correlation coefficient matrix information of the variables used in the baseline regression in our paper. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	<i>RML</i>	<i>RetVol</i>	<i>LoglRetVol</i>	<i>TDA</i>	<i>ROAchange</i>	<i>EventYear</i>	<i>IndustLev</i>	<i>Mktbk</i>	<i>Tangibility</i>	<i>Profit</i>	<i>Assets</i>	<i>FirmAge</i>	<i>Labor</i>	<i>Unemployment</i>	<i>Population</i>	<i>GDPgrowthrate</i>	<i>Tax</i>
<i>RML</i>	1.000																
<i>RetVol</i>	0.055***	1.000															
<i>LoglRetVol</i>	0.061***	0.989***	1.000														
<i>TDA</i>	0.025***	0.036***	0.037***	1.000													
<i>ROAchange</i>	-0.003	0.001	0.000	-0.007*	1.000												
<i>EventYear</i>	0.472***	0.034***	0.037***	-0.008*	0.001	1.000											
<i>IndustLev</i>	-0.110***	-0.035***	-0.037***	0.315***	-0.004	-0.061***	1.000										
<i>Mktbk</i>	-0.003	0.008*	0.009**	0.003	-0.002	-0.001	-0.003	1.000									
<i>Tangibility</i>	-0.061***	-0.023***	-0.023***	0.314***	-0.002	-0.045***	0.214***	0.006	1.000								
<i>Profit</i>	-0.090***	-0.271***	-0.288***	0.029***	-0.027***	-0.046***	0.104***	-0.005	0.101***	1.000							
<i>Assets</i>	-0.015***	-0.402***	-0.435***	0.230***	-0.017***	-0.026***	0.340***	-0.011***	0.123***	0.320***	1.000						
<i>FirmAge</i>	0.020***	-0.220***	-0.237***	0.028***	0.003	-0.042***	0.103***	0.004	0.109***	0.166***	0.294***	1.000					
<i>Labor</i>	0.008*	0.019***	0.021***	-0.019***	-0.002	0.020***	-0.044***	-0.002	-0.051***	-0.008**	-0.061***	-0.027***	1.000				
<i>Unemployment</i>	-0.217***	0.110***	0.120***	-0.091***	0.003	-0.059***	-0.001	-0.006	-0.039***	0.020***	-0.070***	-0.118***	-0.004	1.000			
<i>Population</i>	0.124***	0.073***	0.078***	-0.025***	0.005	0.046***	-0.125***	-0.003	-0.085***	-0.063***	-0.069***	-0.088***	0.016***	0.202***	1.000		
<i>GDPgrowthrate</i>	0.029***	-0.040***	-0.043***	-0.001	0.009**	-0.024***	-0.005	-0.000	0.020***	0.006	0.007*	0.021***	-0.004	-0.072***	0.087***	1.000	
<i>Tax</i>	0.180***	0.053***	0.056***	-0.015***	0.006	0.058***	-0.129***	-0.002	-0.093***	-0.073***	-0.064***	-0.069***	0.018***	0.098***	0.967***	0.095***	1.000

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Cox Model

This table presents the estimation of a Cox proportional hazards model to examine whether the timing of state recreational marijuana laws (RMLs) adoption is associated with macroeconomic and social conditions. The event is a state's first RMLs adoption; the analysis is conducted at the state-year level, where states remain in the risk set until adoption. The explanatory variables include *GDP* (from the Bureau of Economic Analysis (BEA)), *GDPgrowthrate* (constructed from BEA GDP data), *Unemployment* (from Local Area Unemployment Statistics (LAUS) of the Bureau of Labor Statistics (BLS)), *Crime* (crime rate per thousand population from the Federal Bureau of Investigation (FBI)), and *Carbon* (CO₂ emissions in million metric tons from the U.S. Energy Information Administration (EIA)). Year fixed effects are included in the regression. Numbers in parentheses are Wald z-statistics computed using robust standard errors clustered at the state level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Model 1
Variables	Cox
<i>GDP</i>	0.073 (0.47)
<i>GDPgrowthrate</i>	58.680 (0.93)
<i>Unemployment</i>	-0.029 (-0.09)
<i>Crime</i>	0.000 (0.38)
<i>Carbon</i>	-0.024 (-1.48)
Year FE	Yes
<i>N</i>	748

Table 4. Regression Analysis of Leverage

This table presents regression analysis of leverage with propensity-score matching. Dependent variable is *TDA*, where the ratio of total debt to assets. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We also control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2
Variables	TDA	TDA
<i>RML</i>	0.020*** (2.72)	0.017** (2.30)
<i>EventYear</i>	-0.014*** (-2.79)	-0.011** (-2.22)
<i>IndustLev</i>	0.229*** (13.98)	0.229*** (14.00)
<i>Mktbk</i>	0.000*** (2.96)	0.000*** (3.07)
<i>Tangibility</i>	0.212*** (7.54)	0.211*** (7.53)
<i>Profit</i>	-0.047*** (-4.30)	-0.047*** (-4.33)
<i>Assets</i>	0.031*** (4.65)	0.031*** (4.65)
<i>FirmAge</i>	-0.001 (-0.03)	-0.001 (-0.03)
<i>Labor</i>	0.036** (2.53)	0.035** (2.31)
<i>Unemployment</i>		-0.001 (-0.39)
<i>GDPgrowthrate</i>		0.069 (0.70)
<i>Tax</i>		0.041** (2.09)
<i>Population</i>		-0.042* (-1.89)
Constant	-0.077 (-0.58)	0.146 (0.61)
Firm FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	65,395	65,395
Adj. R ²	0.760	0.760

Table 5. Channel Test: Tobacco Tax

This table presents regression analyses of leverage for subsamples stratified by tobacco tax. Dependent variable is *TDA*, where the ratio of total debt to assets. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4
Variables	Low TobaccoTax	High TobaccoTax	Low TobaccoTax	High TobaccoTax
<i>RML</i>	0.028*** (2.67)	0.017 (1.62)	0.025** (2.28)	0.012 (1.24)
Constant	-0.007 (-0.04)	-0.117 (-0.57)	-0.133 (-0.17)	-0.373 (-0.60)
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	35,491	29,904	35,491	29,904
Adj.R ²	0.779	0.761	0.779	0.761

Table 6. Channel Test: Technology Firms

This table presents regression analyses of leverage for subsamples stratified by high tech firms. Dependent variable is *TDA*, where the ratio of total debt to assets. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4
Variables	Non Tech	Tech	Non Tech	Tech
<i>RML</i>	0.014*	0.045***	0.011	0.042**
	(1.77)	(2.73)	(1.43)	(2.55)
Constant	-0.064	-0.148	0.075	0.185
	(-0.41)	(-0.62)	(0.27)	(0.39)
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	56,043	9,352	56,043	9,352
Adj.R ²	0.766	0.736	0.767	0.736

Table 7. Channel Test: Executive Compensations

This table presents regression analyses of leverage for subsamples stratified by executive compensations. Dependent variable is *TDA*, where the ratio of total debt to assets. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4
Variables	Low Compensations	High Compensations	Low Compensations	High Compensations
<i>RML</i>	0.028** (2.16)	0.012 (1.09)	0.027** (2.17)	0.011 (1.02)
Constant	0.734*** (3.09)	-0.017 (-0.02)	0.945** (2.52)	0.115 (0.12)
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	16,667	15,945	16,667	15,945
Adj.R ²	0.811	0.804	0.811	0.804

Table 8. Regression Analysis of M&A Activity

This table presents regression analysis of M&A activity with propensity-score matching. Dependent variable is *MAevents* or *DealValue*. *MAevents* is the number of mergers and acquisitions the company will have in next year and *DealValue* is the total value of consideration paid by the acquiror, excluding fees and expenses. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	MAevents	MAevents	MAevents	MAevents	DealValue	DealValue	DealValue	DealValue
<i>RML</i>	-0.010 (-1.17)	-0.010 (-1.16)	-0.007 (-0.79)	-0.007 (-0.79)	21.434 (1.01)	22.394 (1.08)	29.818 (1.14)	30.861 (1.20)
<i>TDA</i>			0.052** (2.43)	0.053** (2.45)			57.648** (2.22)	57.534** (2.21)
<i>RML</i> × <i>TDA</i>			-0.017 (-0.75)	-0.017 (-0.75)			-37.289 (-0.90)	-37.013 (-0.89)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	65,554	65,554	65,395	65,395	65,554	65,554	65,395	65,395
Adj. R ²	0.248	0.248	0.248	0.248	0.054	0.054	0.054	0.054

Table 9. Regression Analysis of Return Volatility

This table presents regression analysis of return volatility with propensity-score matching. Dependent variable is *RetVol* or *Log1RetVol*, where *RetVol* is the standard deviation of daily stock returns and *Log1RetVol* is natural logarithm of *RetVol*. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	RetVol	RetVol	RetVol	RetVol	Log1RetVol	Log1RetVol	Log1RetVol	Log1RetVol
<i>RML</i>	0.009 (0.38)	0.011 (0.50)	-0.006 (-0.23)	-0.002 (-0.08)	0.008 (0.34)	0.011 (0.47)	-0.007 (-0.27)	-0.003 (-0.10)
<i>TDA</i>			0.455*** (5.95)	0.455*** (5.98)			0.459*** (6.06)	0.458*** (6.09)
<i>RML</i> × <i>TDA</i>			0.023 (0.34)	0.023 (0.34)			0.023 (0.34)	0.024 (0.35)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	65,554	65,554	65,395	65,395	65,554	65,554	65,395	65,395
Adj. R ²	0.735	0.735	0.738	0.738	0.741	0.741	0.743	0.743

Table 10. Regression Analysis of Operating Performance

This table presents regression analysis of operating performance with propensity-score matching. Dependent variable is *ROAchange*, where *ROAchange* is the change in net income between year (*t*) and year (*t-1*), divided by the average total assets over the two periods. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4
Variables	ROAchange	ROAchange	ROAchange	ROAchange
<i>RML</i>	0.006 (0.59)	0.015 (1.60)	0.020 (1.59)	0.030** (2.51)
<i>TDA</i>			0.038 (0.89)	0.041 (0.96)
<i>RML</i> × <i>TDA</i>			-0.062* (-1.78)	-0.063* (-1.80)
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	65,554	65,554	65,395	65,395
Adj.R ²	0.119	0.120	0.119	0.120

Appendix A. Definitions of Variables

Variables	Definition	Data Source
<i>TDA</i>	The ratio of total debt (item 34, debt in current liabilities + item 9, long-term debt) to item 6, assets.	Compustat
<i>RML</i>	It is a dummy variable, equal to one if a state has passed the Recreational Marijuana Laws (RMLs) and the observation falls in the post-treatment period, and zero otherwise.	-
<i>EventYear</i>	A dummy variable that equals to one if recreational marijuana laws were passed in the year and zero otherwise.	-
<i>IndustryLev</i>	The median of total debt to market value of assets by SIC code and by year. Industry is defined at the two-digit SIC code level in the main results. Robustness is examined by redefining industry at the three-digit SIC level.	Compustat
<i>Mktbk</i>	The ratio of MVA to Compustat item 6, assets. MVA is obtained as the sum of the market value of equity (item 199, price-close $\times$ item 54, shares outstanding) + item 34, short-term debt + item 9, long-term debt + item 10, preferred-liquidation value- item 35, deferred taxes and investment tax credit.	Compustat
<i>Tangibility</i>	The ratio of Compustat item 8, net property, plant, and equipment, to item 6, assets.	Compustat
<i>Profit</i>	The ratio of Compustat item 13, operating income before depreciation, to item 6, assets.	Compustat
<i>Assets</i>	Natural logarithm of Compustat item 6, assets deflated to 1992 dollars using the GDP deflator. (\$ bil)	Compustat
<i>FirmAge</i>	The number of years since being included in the Compustat database.	Compustat
<i>Labor</i>	The ratio of the number of employees to property, plant, and equipment and is set to zero in cases where data are not available.	Compustat
<i>Unemployment</i>	Unemployment rate.	Local Area Unemployment Statistics (LAUS) from the Bureau of Labor Statistics (BLS)
<i>GDPgrowthrate</i>	The rate of GDP in the year ($t-1$) and year ($t-2$), scaled by sales in the year ($t-2$).	Bureau of Economic Analysis
<i>Tax</i>	The state-level taxes on production and imports less subsidies.	Bureau of Economic Analysis
<i>Population</i>	Natural logarithm of state-level population.	US Census Bureau and FRED
<i>TobaccoTax</i>	The state tobacco tax revenue.	Urban-Brookings Tax Policy Center (TPC)
<i>Compensations</i>	Total compensation for the individual year comprised of the following: Salary, Bonus, Other Annual, Total Value of Restricted Stock Granted, Net Value of Stock Options Exercised, Long-Term Incentive Payouts, and All Other Total.	Execucomp
<i>MAevents</i>	The number of mergers and acquisitions the company will have in next year.	SDC Platinum
<i>DealValue</i>	Total value of consideration paid by the acquiror, excluding fees and expenses. (\$ mil)	SDC Platinum

<i>RetVol</i>	The standard deviation of daily stock returns.	CRSP
<i>LogRetVol</i>	Natural logarithm of standard deviation of daily stock returns.	CRSP
<i>ROA</i>	The ratio of net income to the book value of assets and is set to zero in cases where data are not available.	Compustat
<i>ROAchange</i>	The change in net income between year (t) and year (t-1), divided by the average total assets over the two periods.	Compustat
<i>Cash</i>	Cash and short-term investments to the book value of assets and is set to zero in cases where data are not available.	Compustat
<i>Crime</i>	Crime rate per thousand population	Federal Bureau of Investigation (FBI)
<i>Carbon</i>	CO2 emissions in million metric tons	U.S. Energy Information Administration (EIA)
<i>Deaths</i>	The number of deaths per 100,000 total population	National Center for Health Statistics

Appendix B. Regression Analysis of Accident Mortality Deaths

This table presents regression analysis of accident mortality deaths with propensity-score matching. Dependent variable is *Deaths*, the number of deaths per 100,000 total population. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2
Variables	Deaths	Deaths
<i>RML</i>	71.262*** (11.15)	62.186*** (12.64)
<i>IndustLev</i>	-1.432 (-0.11)	5.066 (0.47)
<i>Mktbk</i>	0.006 (0.72)	0.007 (1.06)
<i>Tangibility</i>	-1.974 (-0.08)	14.857 (0.82)
<i>Profit</i>	-1.997 (-0.36)	-2.824 (-0.60)
<i>Assets</i>	4.735 (1.09)	6.778* (1.93)
<i>FirmAge</i>	11.226 (1.08)	8.752 (1.10)
<i>Labor</i>	-8.381 (-1.58)	-33.335 (-1.42)
<i>Unemployment</i>		2.833** (2.00)
<i>GDPgrowthrate</i>		-104.922 (-0.85)
<i>Tax</i>		189.297*** (11.82)
<i>Population</i>		-32.805 (-1.60)
<i>Constant</i>	169.589 (1.54)	-1,423.290*** (-6.03)
Firm FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	37,931	37,931
Adj. R ²	0.928	0.942

IA1. Regression Analysis of Leverage by Other Matching Methods

This table presents the estimated effect of recreational marijuana laws (RMLs) on firm leverage using alternative matching approaches. Panel A presents regression analysis of leverage without matching. Panel B presents regression analysis of leverage with radius matching. Panel C presents regression analysis of leverage with nearest neighbor matching. Panel D presents regression analysis of leverage with coarsened exact matching. Panel E presents regression analysis of leverage with entropy balance matching. Dependent variable is *TDA*, where the ratio of total debt to assets. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Non-matching		
	Model 1	Model 2
Variables	TDA	TDA
<i>RML</i>	0.015*** (2.68)	0.014** (2.46)
Constant	-0.024 (-0.28)	0.106 (0.67)
Firm Controls	Yes	Yes
Macro Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	50,115	50,115
Adj. R ²	0.135	0.135
Panel B: Radius Matching		
	Model 1	Model 2
Variables	TDA	TDA
<i>RML</i>	0.022*** (2.81)	0.018** (2.38)
Constant	-0.075 (-0.52)	0.131 (0.50)
Firm Controls	Yes	Yes
Macro Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	58,126	58,126
Adj. R ²	0.750	0.751
Panel C: Nearest Neighbor Matching		
	Model 1	Model 2
Variables	TDA	TDA
<i>RML</i>	0.020*** (2.70)	0.017** (2.29)

Constant	-0.078 (-0.59)	0.143 (0.59)
Firm Controls	Yes	Yes
Macro Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	65,542	65,542
Adj. R ²	0.761	0.761
Panel D: Coarsened Exact Matching		
	Model 1	Model 2
Variables	TDA	TDA
<i>RML</i>	0.018** (2.33)	0.016** (2.16)
Constant	0.165 (1.22)	0.282 (1.09)
Firm Controls	Yes	Yes
Macro Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	27,696	27,696
Adj. R ²	0.794	0.794
Panel E: Entropy Balance Matching		
	Model 1	Model 2
Variables	TDA	TDA
<i>RML</i>	0.020*** (2.89)	0.017** (2.57)
Constant	-0.002 (-0.02)	0.075 (0.35)
Firm Controls	Yes	Yes
Macro Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	50,115	50,115
Adj. R ²	0.745	0.745

IA2. Regression Analysis of M&A Activity by Other Matching Methods

This table presents the estimated effect of recreational marijuana laws (RMLs) on firms' M&A activity using alternative matching approaches. Panel A presents regression analysis of M&A activity without matching. Panel B presents regression analysis of M&A activity with radius matching. Panel C presents regression analysis of M&A activity with nearest neighbor matching. Panel D presents regression analysis of M&A activity with coarsened exact matching. Panel E presents regression analysis of M&A activity with entropy balance matching. Dependent variable is *MAevents* or *DealValue*. *MAevents* is the number of mergers and acquisitions the company will have in next year and *DealValue* is the total value of consideration paid by the acquiror, excluding fees and expenses. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Non-matching								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	MAevents	MAevents	MAevents	MAevents	DealValue	DealValue	DealValue	DealValue
<i>RML</i>	0.001 (0.14)	-0.001 (-0.18)	0.004 (0.55)	0.002 (0.26)	10.936 (0.55)	9.545 (0.48)	23.338 (0.97)	22.036 (0.92)
<i>TDA</i>			0.043*** (3.90)	0.042*** (3.88)			77.111*** (3.15)	76.920*** (3.14)
<i>RML</i> × <i>TDA</i>			-0.014 (-0.74)	-0.014 (-0.74)			-53.353 (-1.35)	-53.391 (-1.35)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	50,266	50,266	50,115	50,115	50,266	50,266	50,115	50,115
Adj. R ²	0.003	0.003	0.004	0.004	0.000	0.000	0.000	0.000
Panel B: Radius Matching								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	MAevents	MAevents	MAevents	MAevents	DealValue	DealValue	DealValue	DealValue
<i>RML</i>	-0.013 (-1.43)	-0.014 (-1.40)	-0.009 (-0.94)	-0.009 (-0.93)	10.106 (0.43)	12.134 (0.53)	22.835 (0.77)	25.036 (0.86)
<i>TDA</i>			0.059*** (2.70)	0.059*** (2.72)			63.111** (2.12)	63.183** (2.11)
<i>RML</i> × <i>TDA</i>			-0.025 (-1.12)	-0.025 (-1.11)			-56.103 (-1.25)	-56.176 (-1.25)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	58,269	58,269	58,126	58,126	58,269	58,269	58,126	58,126
Adj. R ²	0.255	0.255	0.255	0.255	0.056	0.056	0.056	0.056

Panel C: Nearest Neighbor Matching								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	MAevents	MAevents	MAevents	MAevents	DealValue	DealValue	DealValue	DealValue
<i>RML</i>	-0.010 (-1.16)	-0.010 (-1.15)	-0.006 (-0.74)	-0.006 (-0.74)	20.198 (0.95)	21.256 (1.03)	28.975 (1.10)	30.115 (1.17)
<i>TDA</i>			0.052** (2.44)	0.053** (2.47)			57.904** (2.25)	57.817** (2.23)
<i>RML</i> × <i>TDA</i>			-0.018 (-0.81)	-0.018 (-0.81)			-38.793 (-0.94)	-38.519 (-0.94)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	65,702	65,702	65,542	65,542	65,702	65,702	65,542	65,542
Adj. R ²	0.248	0.248	0.248	0.248	0.054	0.054	0.054	0.054
Panel D: Coarsened Exact Matching								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	MAevents	MAevents	MAevents	MAevents	DealValue	DealValue	DealValue	DealValue
<i>RML</i>	-0.005 (-0.46)	-0.008 (-0.75)	0.006 (0.49)	0.003 (0.26)	3.892 (0.35)	-2.886 (-0.28)	-6.142 (-0.51)	-12.471 (-0.89)
<i>TDA</i>			0.087*** (3.56)	0.086*** (3.53)			47.130** (2.00)	46.222* (1.95)
<i>RML</i> × <i>TDA</i>			-0.051 (-1.42)	-0.052 (-1.43)			34.709 (0.72)	33.312 (0.70)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	27,770	27,770	27,696	27,696	27,770	27,770	27,696	27,696
Adj. R ²	0.177	0.177	0.178	0.178	-0.004	-0.004	-0.004	-0.004
Panel E: Entropy Balance Matching								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	MAevents	MAevents	MAevents	MAevents	DealValue	DealValue	DealValue	DealValue
<i>RML</i>	-0.006 (-0.77)	-0.006 (-0.87)	-0.003 (-0.42)	-0.004 (-0.53)	9.805 (0.44)	10.306 (0.47)	20.112 (0.73)	20.665 (0.76)
<i>TDA</i>			0.047*** (3.26)	0.047*** (3.23)			67.331*** (2.60)	67.310*** (2.60)
<i>RML</i> × <i>TDA</i>			-0.013 (-0.59)	-0.012 (-0.56)			-45.261 (-1.10)	-45.009 (-1.10)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	50,266	50,266	50,115	50,115	50,266	50,266	50,115	50,115
Adj. R ²	0.262	0.262	0.262	0.262	0.014	0.014	0.014	0.013

IA3. Regression Analysis of Return Volatility by Other Matching Methods

This table presents the estimated effect of recreational marijuana laws (RMLs) on firms' return volatility using alternative matching approaches. Panel A presents regression analysis of return volatility without matching. Panel B presents regression analysis of return volatility with radius matching. Panel C presents regression analysis of return volatility with nearest neighbor matching. Panel D presents regression analysis of return volatility with coarsened exact matching. Panel E presents regression analysis of return volatility with entropy balance matching. Dependent variable is *RetVol* or *Log1RetVol*, where *RetVol* is the standard deviation of daily stock returns and *Log1RetVol* is natural logarithm of *RetVol*. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Non-matching								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	RetVol	RetVol	RetVol	RetVol	Log1RetVol	Log1RetVol	Log1RetVol	Log1RetVol
<i>RML</i>	-0.021 (-1.20)	-0.022 (-1.20)	-0.015 (-0.69)	-0.015 (-0.67)	-0.022 (-1.25)	-0.022 (-1.23)	-0.016 (-0.73)	-0.015 (-0.70)
<i>TDA</i>			0.568*** (13.48)	0.567*** (13.48)			0.571*** (13.73)	0.571*** (13.73)
<i>RML</i> × <i>TDA</i>			-0.058 (-1.04)	-0.057 (-1.02)			-0.058 (-1.05)	-0.057 (-1.03)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	50,233	50,233	50,082	50,082	50,233	50,233	50,082	50,082
Adj. R ²	0.361	0.362	0.370	0.370	0.371	0.371	0.380	0.380
Panel B: Radius Matching								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	RetVol	RetVol	RetVol	RetVol	Log1RetVol	Log1RetVol	Log1RetVol	Log1RetVol
<i>RML</i>	0.004 (0.16)	0.009 (0.37)	-0.012 (-0.41)	-0.005 (-0.17)	0.003 (0.11)	0.008 (0.34)	-0.013 (-0.46)	-0.006 (-0.20)
<i>TDA</i>			0.456*** (5.37)	0.456*** (5.40)			0.459*** (5.47)	0.459*** (5.50)
<i>RML</i> × <i>TDA</i>			0.026 (0.34)	0.025 (0.33)			0.026 (0.34)	0.026 (0.34)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	58,269	58,269	58,126	58,126	58,269	58,269	58,126	58,126
Adj. R ²	0.733	0.733	0.735	0.736	0.739	0.739	0.741	0.741

Panel C: Nearest Neighbor Matching								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	RetVol	RetVol	RetVol	RetVol	Log1RetVol	Log1RetVol	Log1RetVol	Log1RetVol
<i>RML</i>	0.008 (0.35)	0.011 (0.48)	-0.007 (-0.26)	-0.003 (-0.10)	0.007 (0.32)	0.010 (0.45)	-0.008 (-0.30)	-0.003 (-0.13)
<i>TDA</i>			0.455*** (5.98)	0.455*** (6.00)			0.459*** (6.08)	0.458*** (6.11)
<i>RML</i> × <i>TDA</i>			0.024 (0.35)	0.024 (0.36)			0.024 (0.36)	0.025 (0.37)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	65,702	65,702	65,542	65,542	65,702	65,702	65,542	65,542
Adj. R ²	0.736	0.736	0.738	0.739	0.741	0.742	0.744	0.744
Panel D: Coarsened Exact Matching								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	RetVol	RetVol	RetVol	RetVol	Log1RetVol	Log1RetVol	Log1RetVol	Log1RetVol
<i>RML</i>	0.002 (0.09)	0.008 (0.29)	-0.005 (-0.14)	0.001 (0.03)	0.001 (0.04)	0.007 (0.24)	-0.007 (-0.19)	-0.000 (-0.01)
<i>TDA</i>			0.514*** (7.15)	0.516*** (7.18)			0.520*** (7.29)	0.521*** (7.32)
<i>RML</i> × <i>TDA</i>			-0.003 (-0.03)	-0.002 (-0.02)			-0.003 (-0.03)	-0.001 (-0.01)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	27,766	27,766	27,692	27,692	27,766	27,766	27,692	27,692
Adj. R ²	0.735	0.735	0.738	0.738	0.740	0.740	0.743	0.743
Panel E: Entropy Balance Matching								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Variables	RetVol	RetVol	RetVol	RetVol	Log1RetVol	Log1RetVol	Log1RetVol	Log1RetVol
<i>RML</i>	-0.005 (-0.27)	-0.005 (-0.25)	-0.012 (-0.51)	-0.011 (-0.43)	-0.006 (-0.31)	-0.006 (-0.27)	-0.013 (-0.55)	-0.011 (-0.45)
<i>TDA</i>			0.501*** (8.69)	0.501*** (8.71)			0.504*** (8.86)	0.504*** (8.88)
<i>RML</i> × <i>TDA</i>			-0.008 (-0.13)	-0.009 (-0.14)			-0.009 (-0.14)	-0.009 (-0.14)

Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	50,233	50,233	50,082	50,082	50,233	50,233	50,082	50,082
Adj. R ²	0.704	0.704	0.707	0.708	0.710	0.710	0.714	0.714

IA4. Regression Analysis of Operating Performance by Other Matching Methods

This table presents the estimated effect of recreational marijuana laws (RMLs) on firms' operating performance using alternative matching approaches. Panel A presents regression analysis of operating performance without matching. Panel B presents regression analysis of operating performance with radius matching. Panel C presents regression analysis of operating performance with nearest neighbor matching. Panel D presents regression analysis of operating performance with coarsened exact matching. Panel E presents regression analysis of operating performance with entropy balance matching. Dependent variable is *ROAchange*, where *ROAchange* is the change in net income between year (*t*) and year (*t-1*), divided by the average total assets over the two periods. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Non-matching				
	Model 1	Model 2	Model 3	Model 4
Variables	ROAchange	ROAchange	ROAchange	ROAchange
<i>RML</i>	0.001 (0.20)	0.003 (0.39)	0.003 (0.25)	0.005 (0.37)
<i>TDA</i>			-0.075** (-2.56)	-0.074** (-2.54)
<i>RML</i> × <i>TDA</i>			-0.005 (-0.17)	-0.007 (-0.21)
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	50,266	50,266	50,115	50,115
Adj. R ²	0.029	0.029	0.029	0.029
Panel B: Radius Matching				
	Model 1	Model 2	Model 3	Model 4
Variables	ROAchange	ROAchange	ROAchange	ROAchange
<i>RML</i>	-0.005 (-0.37)	0.004 (0.35)	0.000 (0.02)	0.010 (0.54)
<i>TDA</i>			-0.088 (-1.22)	-0.085 (-1.19)
<i>RML</i> × <i>TDA</i>			-0.014 (-0.28)	-0.016 (-0.33)
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	58,269	58,269	58,126	58,126
Adj. R ²	0.137	0.137	0.137	0.137

Panel C: Nearest Neighbor Matching				
	Model 1	Model 2	Model 3	Model 4
Variables	ROAchange	ROAchange	ROAchange	ROAchange
<i>RML</i>	-0.001 (-0.08)	0.007 (0.62)	0.006 (0.33)	0.014 (0.85)
<i>TDA</i>			-0.070 (-1.11)	-0.068 (-1.08)
<i>RML</i> × <i>TDA</i>			-0.024 (-0.59)	-0.026 (-0.63)
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	65,702	65,702	65,542	65,542
Adj. R ²	0.144	0.144	0.144	0.144
Panel D: Coarsened Exact Matching				
	Model 1	Model 2	Model 3	Model 4
Variables	ROAchange	ROAchange	ROAchange	ROAchange
<i>RML</i>	-0.003 (-0.40)	-0.000 (-0.05)	-0.003 (-0.26)	-0.001 (-0.05)
<i>TDA</i>			-0.093*** (-4.46)	-0.093*** (-4.45)
<i>RML</i> × <i>TDA</i>			0.006 (0.20)	0.006 (0.19)
Firm Controls	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	27,770	27,770	27,696	27,696
Adj. R ²	0.254	0.255	0.258	0.259
Panel E: Entropy Balance Matching				
	Model 1	Model 2	Model 3	Model 4
Variables	ROAchange	ROAchange	ROAchange	ROAchange
<i>RML</i>	0.001 (0.15)	0.006 (0.73)	0.008 (0.62)	0.012 (1.04)
<i>TDA</i>			-0.058 (-1.56)	-0.057 (-1.55)
<i>RML</i> × <i>TDA</i>			-0.024 (-0.71)	-0.024 (-0.73)
Firm Controls	Yes	Yes	Yes	Yes

Macro Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	50,266	50,266	50,115	50,115
Adj. R ²	0.106	0.106	0.106	0.106

IA5. Regression Analysis of Actual Buyback Ratio

This table presents regression analysis of actual buyback ratio with propensity score matching. The dependent variable, *Buyback*, is defined following Banyi et al. (2008) as Compustat's purchase of common and preferred stock minus any decrease in redeemable preferred stock, scaled by shares outstanding. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2
Variables	Buyback	Buyback
<i>RML</i>	-0.183 (-0.74)	-0.224 (-0.94)
<i>EventYear</i>	0.305 (1.35)	0.354 (1.50)
<i>IndustLev</i>	-2.037** (-2.20)	-2.063** (-2.24)
<i>Mktbk</i>	1.995 (0.60)	2.037 (0.62)
<i>Tangibility</i>	-0.824 (-1.10)	-0.818 (-1.08)
<i>Profit</i>	-1.345 (-0.63)	-1.375 (-0.65)
<i>Assets</i>	0.162 (0.64)	0.168 (0.66)
<i>FirmAge</i>	0.000 (0.01)	-0.004 (-0.15)
<i>Labor</i>	-2.976 (-0.29)	-2.460 (-0.24)
<i>Unemployment</i>		-0.010 (-0.26)
<i>GDPgrowthrate</i>		-1.596 (-1.04)
<i>Tax</i>		0.434 (1.29)
<i>Population</i>		-0.274 (-0.78)
Constant	0.337 (0.18)	0.088 (0.03)
Firm FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	1,397	1,397
Adj. R ²	0.137	0.137

IA6. Regression Analysis of Leverage with Finance and Utility Firms

This table presents regression analysis of leverage with finance and utility firms, besides using propensity-score matching. Dependent variable is *TDA*, where the ratio of total debt to assets. *RML* is a dummy variable equal to 1 for firms headquartered in states that have passed RMLs during the post-legalization period, and 0 otherwise. Other control variables are defined in Appendix A. We also control for firm fixed-effect and year fixed-effect in each regression. Numbers in parentheses are t-statistics using standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2
Variables	TDA	TDA
<i>RML</i>	0.023*** (2.67)	0.019** (2.18)
<i>EventYear</i>	-0.015** (-2.56)	-0.011* (-1.93)
<i>IndustLev</i>	0.211*** (9.56)	0.211*** (9.55)
<i>Mktbk</i>	0.000 (0.80)	0.000 (0.95)
<i>Tangibility</i>	0.204*** (6.05)	0.204*** (6.05)
<i>Profit</i>	-0.027 (-1.55)	-0.027 (-1.55)
<i>Assets</i>	0.037*** (5.68)	0.036*** (5.61)
<i>FirmAge</i>	-0.012 (-0.87)	-0.012 (-0.91)
<i>Labor</i>	0.013 (1.05)	0.013 (1.03)
<i>Unemployment</i>		0.001 (0.28)
<i>GDPgrowthrate</i>		0.152 (0.97)
<i>Tax</i>		0.058** (2.47)
<i>Population</i>		-0.061** (-2.26)
Constant	-0.022 (-0.25)	0.317 (1.26)
Firm FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	52,745	52,745
Adj. R ²	0.745	0.746